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Forecasting Foodgrains Production Using Arima Model and Neural Network

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Abstract: The time series is a set of values arranged in a specific order of time. Prediction and analysis of food grain is a vital role in agriculture statistics. The Agriculture Statistics System is very complete and provides data on a wide range of topics such as crop area and production, land use, irrigation, land holdings, agricultural prices and market intelligence, livestock, fisheries, forestry etc. Agricultural credit and subsidies also consider important supporting factors for agricultural growth. India is the world's largest producer of millets and second-largest producer of wheat, rice, and pulses. The present research work focused on production of food grains in India using time series data ranging from 1990- 91 to 2018-19. In this paper, Autoregressive Integrated Moving Average Model (ARIMA), Multilayer Perceptron (MLP) and Radial Basis Function (RBF) for predicting foodgrains of India were compared. Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) were compared. The results were displayed numerically and graphically.

Keywords: ARIMA, MLP, RBF, MAE, MAPE and Residual Analysis

1. Introduction

Time series refers to an arrangement and presentation of statistical data in chronological order. Time series mainly used for forecasting. The time series forecast can deal with many forecasting problems. Food grain production covers leading part in Indian agriculture. Agriculture is very vital sector to develop the economy. Agriculture is a vital role in the Indian economy. Agricultural Statistics System mainly based on crop and land usage. Crop production contains grains, cotton, tobacco, fruits, vegetables, nuts and plants. Different crops grow in different areas of the country. Forecasting predict the future values based on past records. Hiransha et al [5] predicted the stock price of a company using Multilayer Perceptron (MLP), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN). Vinayakumar R, et al [12] predicted the meteorological data using Recurrent neural network (RNN) and Long short term memory (LSTM). Athira et al [1] used for forecasting, based on the pollution and meteorological time series AirNet data. Razak et al [9] predicted the maximum demand of electric time series model. Osman Hegazy et al [8] proposed least square support vector machine (LS-SVM) a machine learning model to predict stock market price. Selvin et al [9] designed to identify an underlying trend from a data and to generalize from it. ANN's are considered as a non-linear statistical data tool. In this paper, Autoregressive Integrated Moving Average Model (ARIMA), neural networks for Multilayer Perceptron (MLP) and Radial Basis Function (RBF) were used for foodgrains production prediction in India during 1991 to 2019. The performance of these different models was evaluated using the forecasting accuracy criteria, namely, the Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE).

Review of Literature

Heaton et al. [3] applied deep-learning models for financial forecasting. Box et al [2] engaged multiple linear regression (MLR) methods are used in air quality predictions. Xingjian et al. [15] proposed RNN and convolutional LSTM to figure the precipitation in future two hours, which they formalized as a spatio-temporal issue. Menon et al [6] employed Auto Regressive

Integrated Moving Average model (ARIMA) used for stock market forecasting. Viswam and Satyanarayana Reddy [13] predicted short term share market using Autoregressive Integrated Moving Average (ARIMA) model. Wanie et al [14] predicted rainfall data in Tasik Kenyir using neural networks. Moulana et al [7] predicted short term rainfall and long term rainfall using machine learning methods. Suresh et Al [11] presented distribution based length of interval is used for forecasting the accidents occurred in India.

2. Methodology

Time series analysis is used for analyzing time series data. Time series forecasting to forecast future events based on past events.

2.1. Autocorrelation Function (ACF)

Autocorrelation is a special case of correlation. Its successive values of the same variable based on time.

$$r_p = \frac{\sum_{t=1}^{n-p}\left(Y_t - \overline{Y}\right)\left(Y_{t-p} - \overline{Y}\right)}{\sum_{t=1}^{n}\left(Y_t - \overline{Y}\right)} \quad (1)$$

It ranges from -1 to +1.

2.2. Partial Autocorrelation Function (PACF)

Partial autocorrelations are used to measure the degree of association between Y_t and Y_{t-p} when the effects of other time lags (1, 2, …, p-1) are removed. Partial autocorrelation coefficient of order p is denoted by b_p and can be calculated by regressing Y_t against $Y_{t-1}, \ldots, Y_{t-p}$.

$$Y_t = b_0 + b_1 Y_{t-1} + b_2 Y_{t-2} + \ldots + b_p Y_{t-p} \quad (2)$$

2.3. Autoregressive (AR) Model

If we model Y_t as the model Y_t is

$$(Y_t - \delta) = (Y_{t-1} - \delta) + \alpha_2 (Y_{t-2} - \delta) + \ldots + \alpha_p (Y_{t-p} - \delta) + u_t \quad (3)$$

Where δ is the mean of Y and where u_t is an uncorrelated random error term with zero mean and constant variance σ^2

2.4. Moving Average (MA) Model

The moving average process is simply a linear combination of white noise error terms.

The model Y is as follows

$$Y_t = \mu + \beta_0 u_t + \beta_1 u_{t-1} + \beta_2 u_{t-2} + \ldots + \beta_q u_{t-q} \quad (4)$$

Where μ is a constant and u is the white noise stochastic error term.

2.5. Autoregressive Moving Average (ARMA) Model

The process of both AR and MA and is therefore ARMA. Thus, Y_t follows an ARMA (p,q) process if it can be written as,

$$Y_t = \theta + \alpha_1 Y_{t-1} + \beta_0 u_t + \beta_1 u_{t-1} + \alpha_2 Y_{t-2} + \beta_2 u_{t-2} + \cdots + \alpha_p Y_{t-p} + \beta_q u_{t-q}$$

where p is a autoregressive and q is a moving average term. θ represents a constant term.

2.6. Autoregressive Integrated Moving Average Model (ARIMA)

Autoregressive Integrated Moving Average Model (p, d, q), where p is Autoregressive and q is the Moving Average Model and d is the differencing. If d=0, the data exhibits stationary and the order is denoted as (p, q), which is called ARMA process. If the data does not exhibit stationary, the first order differencing is carried out for converting it into stationary, hence the model is denoted as (p, d, q).

2.7. Box Jenkins Methodology

The schematic representation of Box-Jenkins ARIMA methodology is shown in the following diagram

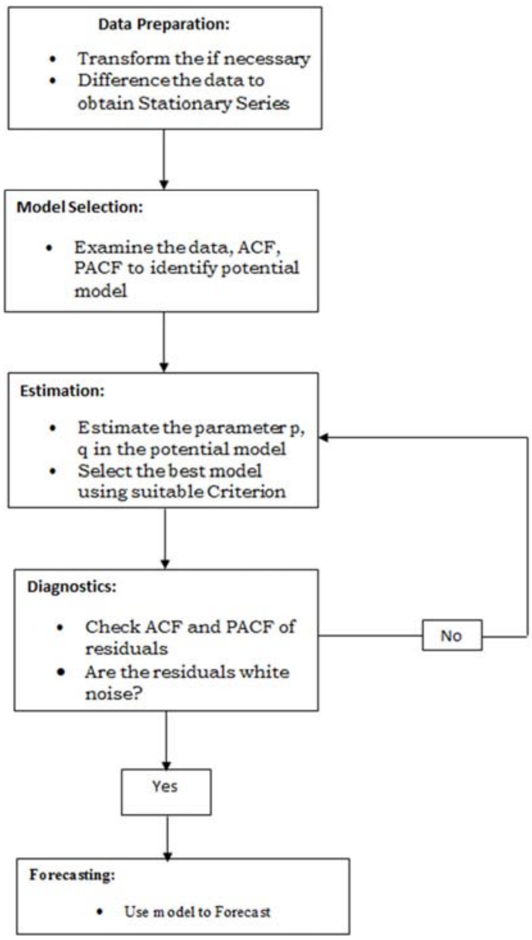


Figure 1. *Systematic Representation of Box-Jenkins Methodology for Time Series.*

2.8. Radial Basis Function (RBF)

It contains three layers namely, input layer, hidden layer and output layer. Input layer is made of source nodes that connect the network to its environment. Second is the hidden layer which applies a nonlinear transformation from the input space to the hidden space, which is of high dimensionality. Output layer is linear, supplying the response of the network to the activation patterns applied to the input layer. The RBF output layer results in a linear fashion. The output y is computed by

$$y_i(x) = \sum_{k=1}^{J} W_{ki}\varphi\left(\left\|X - C_k\right\|\right) \quad (5)$$

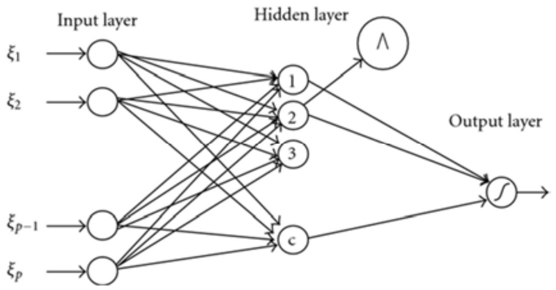


Figure 2. *General Architecture of RBF Network.*

2.9. Multi_Layer Perceptron (MLP)

Multi Layer Perceptron (MLP) has many layers, the first layer is the input layer, the last layer is the output layer, the middle layers are called hidden layers, each layer includes several neurons. Each node value is calculated using the following formula

$$X_{ij}=f(WX_{i-1}+b_{i-1}) \quad (6)$$

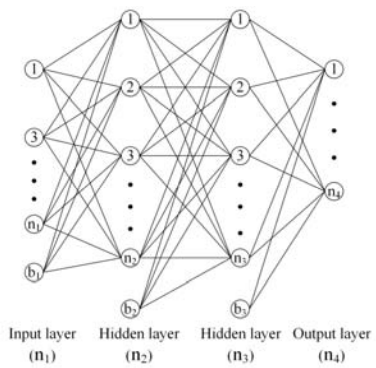


Figure 3. *General Architecture of MLP Network.*

2.10. Residual Analysis

Residuals are differences between actual value and estimated value.

Mean Absolute Error (or Deviation) (MAE or MAD)

The arithmetic average of the absolute errors, where is the prediction and. the true value.

$$\text{MAE}=\frac{1}{n}\sum_{t=1}^{n}\left|u_t\right| \quad (7)$$

Where $u_t = y_t - \hat{y}_t$

$\hat{y}_t$ =prediction

y_t =true value

n=number of observations

Mean Absolute Percentage Error (MAPE)

The mean absolute percentage error (MAPE) is a statistical measure of how accurate a forecast system is it measures this accuracy as a percentage, and can be calculated as the average absolute percent error for each time period minus actual values divided by actual values.

The mean absolute percentage error is given by

$$\text{MAPE}==\frac{1}{n}\sum_{t=1}^{n}\left|\frac{Y_t - F_t}{Y_t}\right|100 \quad (8)$$

Y_t =Actual Value

F_t =Estimated value

n=number of observations

3. Results and Discussion

We have implemented the analysis in foodgrains production of India during the year 1991- 2019. The data are taken from Http//: Agricoop. Conic. In. For the analysis data from 1991 to 2019 is considered. The data consist of the foodgrains production of India. For this we had used ARIMA, neural networks, namely, RBF and MLP. In this work we have considered foodgrains production of prediction for ARIMA and neural networks. The results obtained are as follows.

3.1. Analysis of Foodgrains Production Using ARIMA

ARIMA model seems to be the best fit and also forecasting has been done. The Non-stationary of the data is viewed from the following line graph.

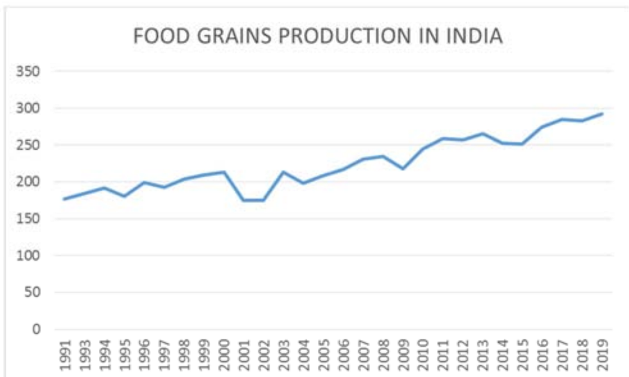
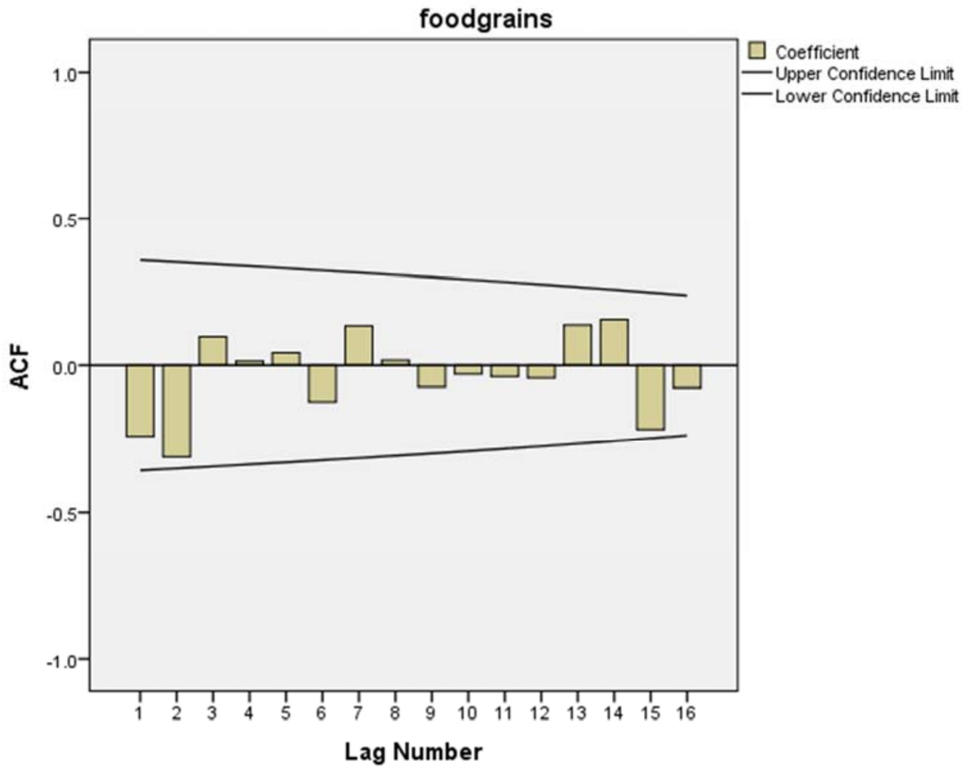


Figure 4. *Non Stationary for Line Graph.*

3.2. ACF and PACF Foodgrains Production

In order to make the points stationary, first order differencing carried out. Below the graphs give the details on the first order differencing.



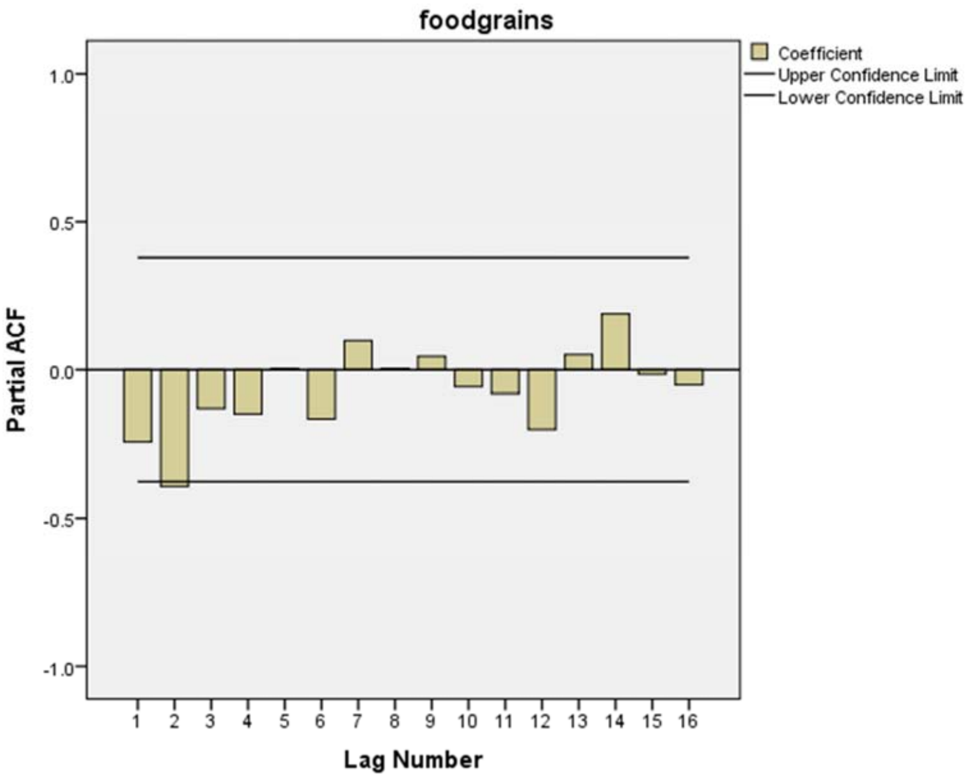


Figure 5. *Autocorrelation and Partial Autocorrelation graphs for first order differencing.*

Table 1. *Box- Ljung Statistic.*

Autocorrelations					
Series: foodgrains					
Lag	Autocorrelation	Std. Error[a]	Box-Ljung Statistic		
			Value	df	Sig.[b]
1	-.242	.179	1.827	1	.176
2	-.312	.176	4.971	2	.083
3	.098	.173	5.291	3	.152
4	.014	.169	5.298	4	.258
5	.042	.165	5.363	5	.373
6	-.124	.162	5.950	6	.429
7	.136	.158	6.691	7	.462
8	.017	.154	6.703	8	.569
9	-.073	.150	6.941	9	.643
10	-.030	.146	6.982	10	.727
11	-.038	.142	7.055	11	.795
12	-.043	.138	7.152	12	.847
13	.139	.134	8.229	13	.828
14	.157	.129	9.715	14	.783
15	-.218	.124	12.797	15	.618
16	-.076	.120	13.204	16	.658

Table 1 shows that the Q value is 13.204 fork=16. We compare this to the Chi square distribution with 16-2=14 degrees of freedom. Here the calculated value is less than the table value, i.e., 13.204< 23.68. It concluded that Q is not significant. The residuals can consider as a white noise series.

Table 2. *BIC Values of ARIMA (p, d, q).*

ARIMA (p,d,q)	Normalized BIC
ARIMA(1,1,0)	5.759
ARIMA(0,1,1,)	5.463
ARIMA(1,1,1)	5.579
ARIMA(2,1,0)	5.725
ARIMA(0,1,2)	5.548

When comparing with other models, the smaller BIC statistic value indicates the better fitting model. The specified order is an ARIMA (0,1,1) and hence the model is fitted and the forecasting is done.

Table 3. *Forecasting using ARIMA Modeel.*

Forecast					
Model		2020	2021	2022	2023
Foodgrains Production	Forecast	301.00	308.65	316.53	324.66
	UCL	327.02	334.75	342.72	350.92
	LCL	274.98	282.55	290.35	298.39

Table 3 shows that forecasted values from 2020 to 2023 values 301 to 324.66 and also upper control limit and lower control limit are calculated.

3.3. ACF and PACF of Food Grains (Residual Analysis)

The residual analysis is carried out using autocorrelations function and partial autocorrelation functions. Below graphs gives the details on the residuals of ACF and PACF.

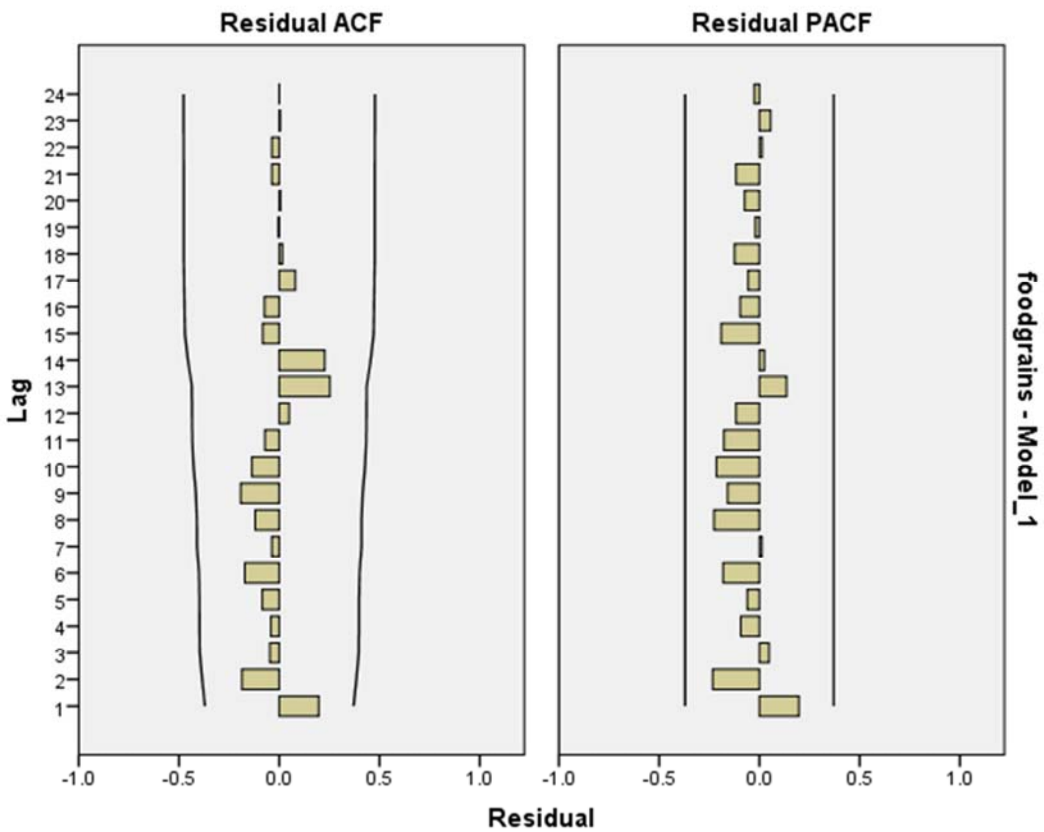


Figure 6. *Autocorrelation and Partial Autocorrelation graphs for Residuals.*

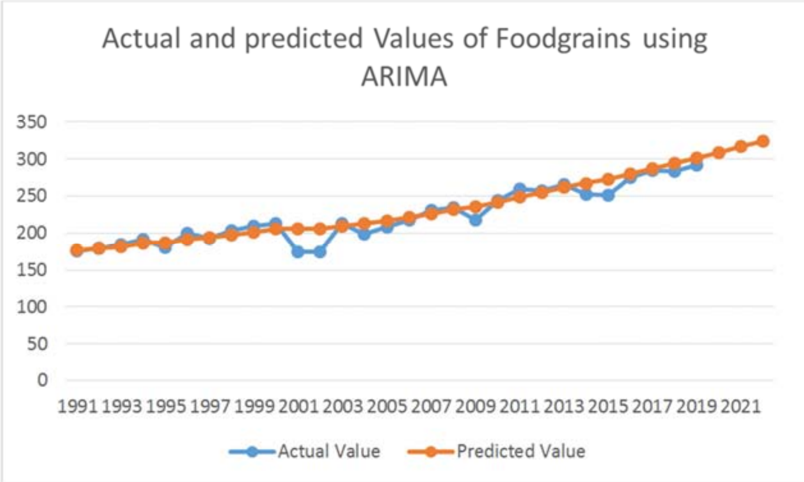


Figure 7. *Actual and Predicted Values of Foodgrains Production using ARIMA Model.*

Figure 7 represents the actual and forecasted values using the ARIMA model.

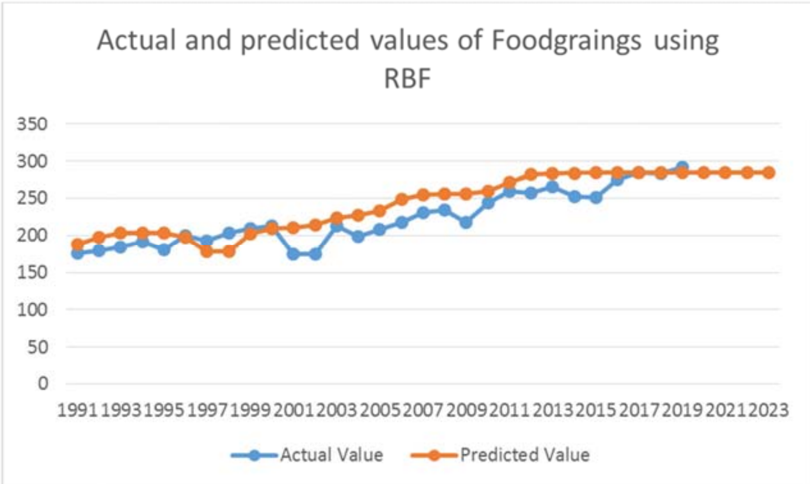


Figure 8. *Actual and Predicted Values of Foodgrains Production using RBF Model.*

Figure 8 represents the actual and forecasted values using the RBF model.

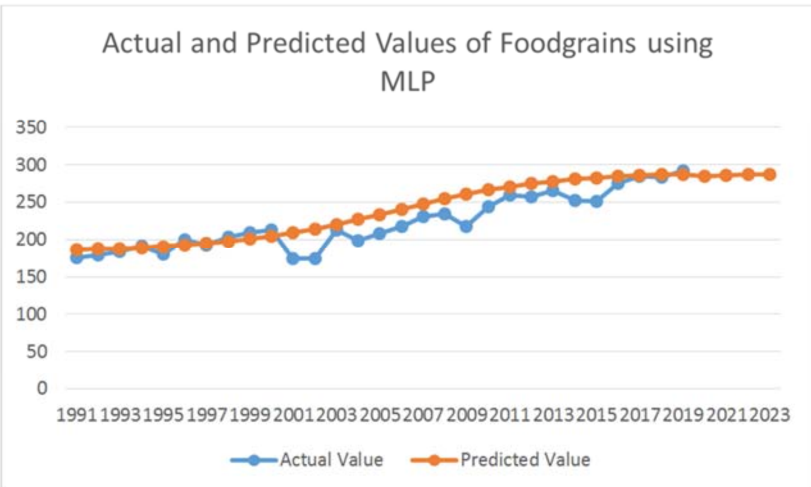


Figure 9. *Actual and Predicted Values of Foodgrains Production using MLP Model.*

Figure 9 represents the actual and forecasted values using the MLP model.

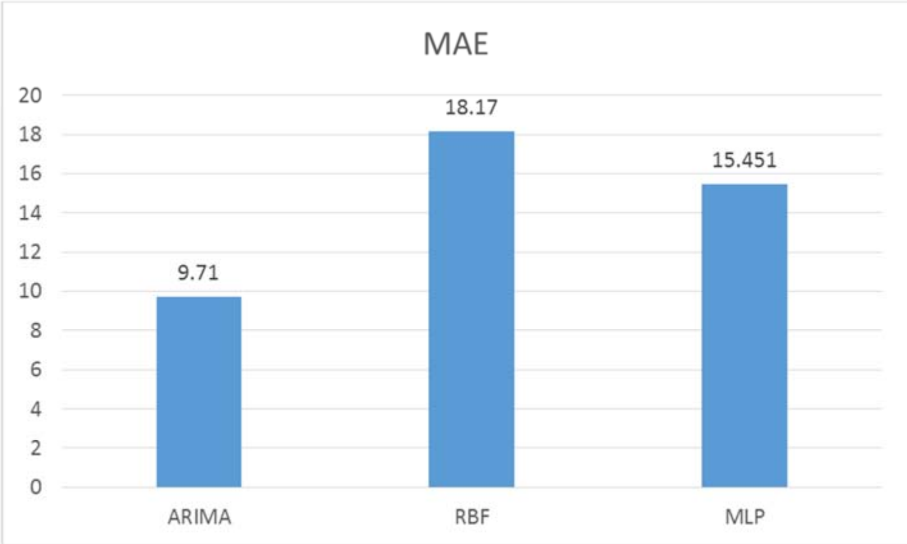


Figure 10. *Mean Absolute Error using ARIMA, RBF and MLP.*

Figure 10 indications the MAE gained by the ARIMA and neural network for foodgrains production prediction. MAE of ARIMA is less value when compared to the neural network. MAE shows that the performance of ARIMA is better than that neural network.

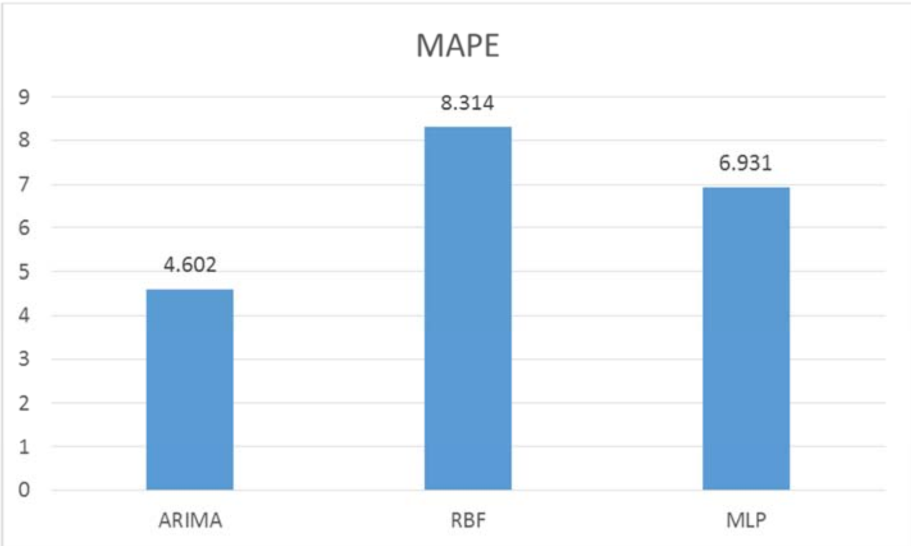


Figure 11. *The Mean Absolute Percentage Error using ARIMA, RBF and MLP.*

Figure 11 displays the MAPE attained by the ARIMA and neural network for foodgrains production prediction. MAPE of ARIMA is less value when compared to the neural network. MAPE shows that the performance of ARIMA is better than that neural network.

4. Conclusion

In this work, three models, namely ARIMA, RBF and MLP were used for foodgrains production prediction in India. Mean absolute error and mean percentage error were compared using bar charts. Mean absolute error and mean absolute percentage error were minimum for ARIMA models when compared to the RBF and MLP. ARIMA model is performed better than that RBF and MLP.

Taking into consideration the Autocorrelation function and Partial Autocorrelation function for food grains, various models have been considered. The best model that fit was the ARIMA models and also forecasted.

The model, ARIMA (0,1,1) was found as the best fit for the food grains with BIC=5.463, when considering the forecasted values, there is an increasing trend pattern from 2019 to 2023 years. The food grains have increased from 301 to 324.66.

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